TUPA29

MACHINE LEARNING FOR PREDICTING POWER SUPPLY TRIPS IN STORAGE RINGS

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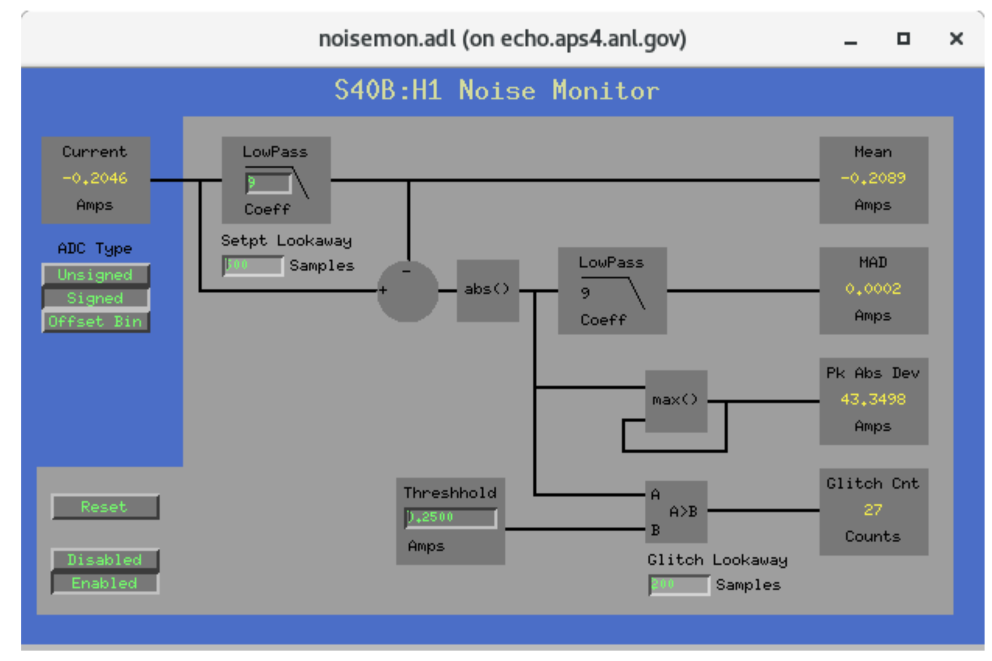
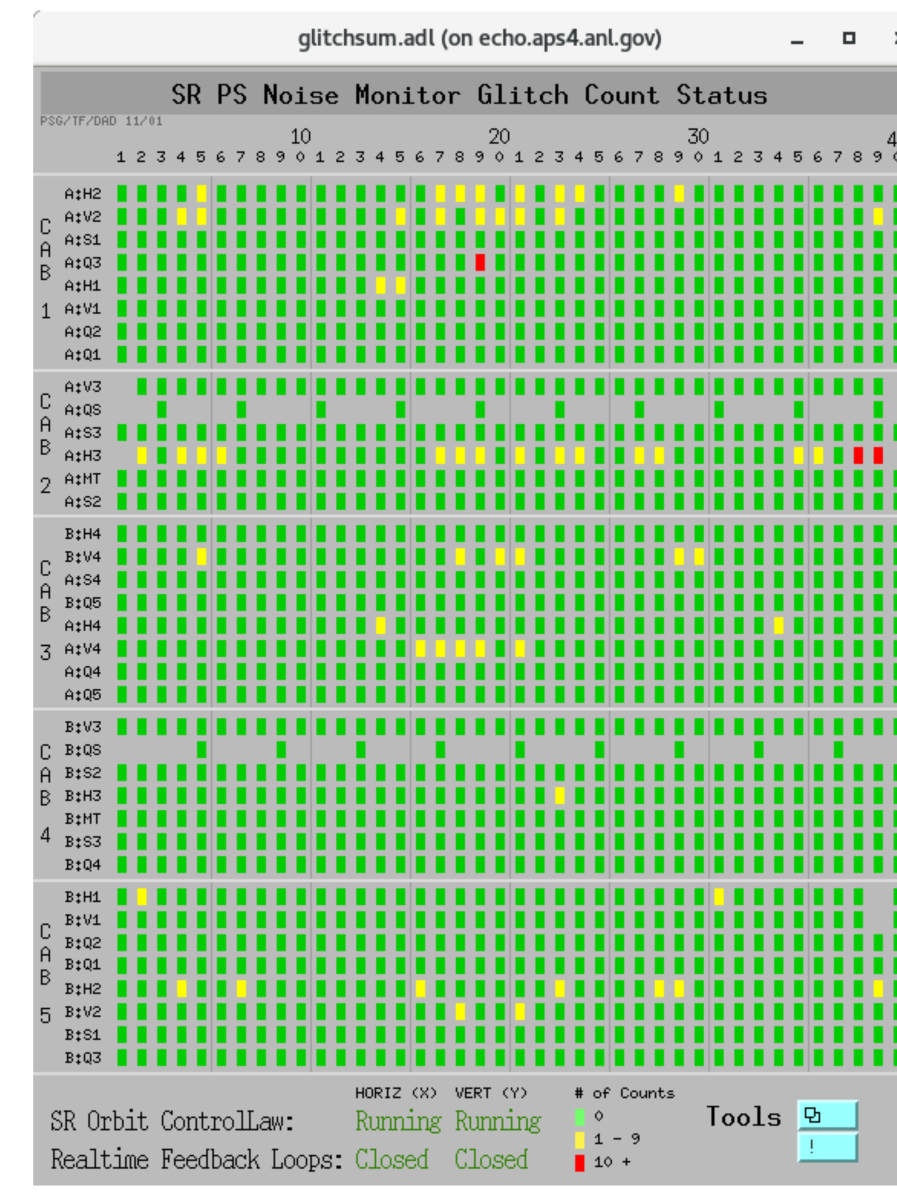
Abstract:
In the Advanced Photon Source (APS) storage ring at Argonne National Lab, trips in the magnet power supplies (PSs) lead to a complete electron beam loss a few times a year. This results in unexpected interruptions of the users' experiments. In this contribution, we investigate the historical data for the last two decades to find precursors for the PS trips that could provide an advance notice for future trips and allow some preventive action by the ring operator or by the PS maintenance team. Various unsupervised anomaly detection models can be trained on the vast amounts of available reference data from the beamtime periods that ended with an intentional beam dump. We find that such models can sometimes detect trip precursors in PS currents, voltages, and in the temperatures of magnets, capacitors and transistors (components of PSs).

Introduction

APS Storage Ring has 40 sectors, each has A and B subsectors. In this contribution, we consider quadrupoles (Q), sextupoles (S), horizontal (H) and vertical (V) correctors (overall, 1320). Example of a magnet name: S40B:H1

We analyzed the APS run history from 2001 to 2022:
- Found 629 ring fills that ended with "Int. Dump: End of Period"
- Found 149 ring fills that ended with a PS trip, glitch, fault, or problem





Available Historical Data:

Process Variable	Explanation
CurrentAI	PS current
MagTempAI	Magnet temperature
CapTempAI	PS capacitor temperature
IGBTTempAI	PS transistor temperature
OutVoltageAI	PS voltage

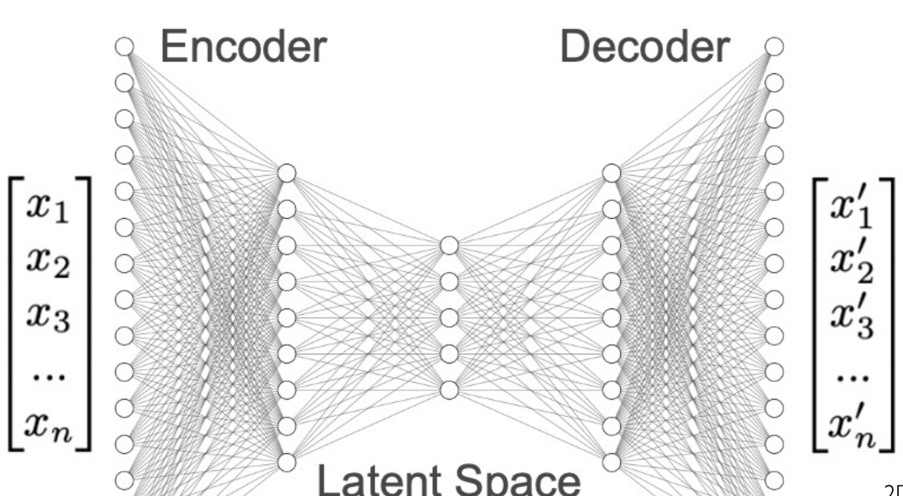
1 point per 64 seconds starting from 2008

PS Current Noise Monitor Data
- Instantaneous Mean Current → MeanMin, MeanMean, MeanMax in a 10 min window
- Instantaneous Mean Absolute Deviation of Current → MADMin, MADMean, MADMax in a 10 min window

1 point per 10 minutes starting from 2001

* For the most recent year, there is 1 point per minute. Older data are down-sampled.

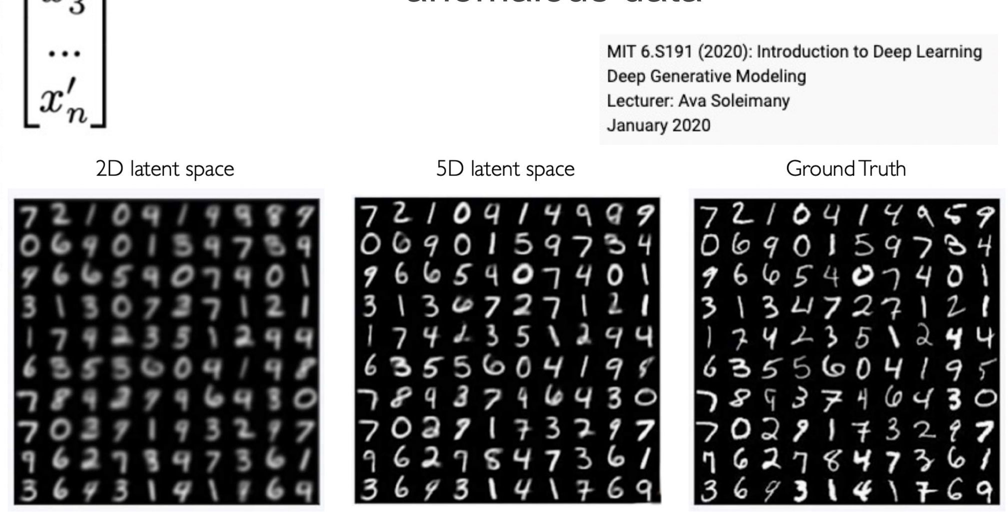
Autoencoders for Anomaly Detection



Training objective: reconstruct input data

If we train an autoencoder on "normal" data, then the reconstruction error will be low for normal data, and (likely) high for anomalous data

$$\mathcal{L}_{\mathrm{MSE}} = \frac{1}{N}\sum_{j=1}^{N}\sum_{i=1}^{n}\left(x_i^{(j)} - x_i'^{(j)}\right)^2$$



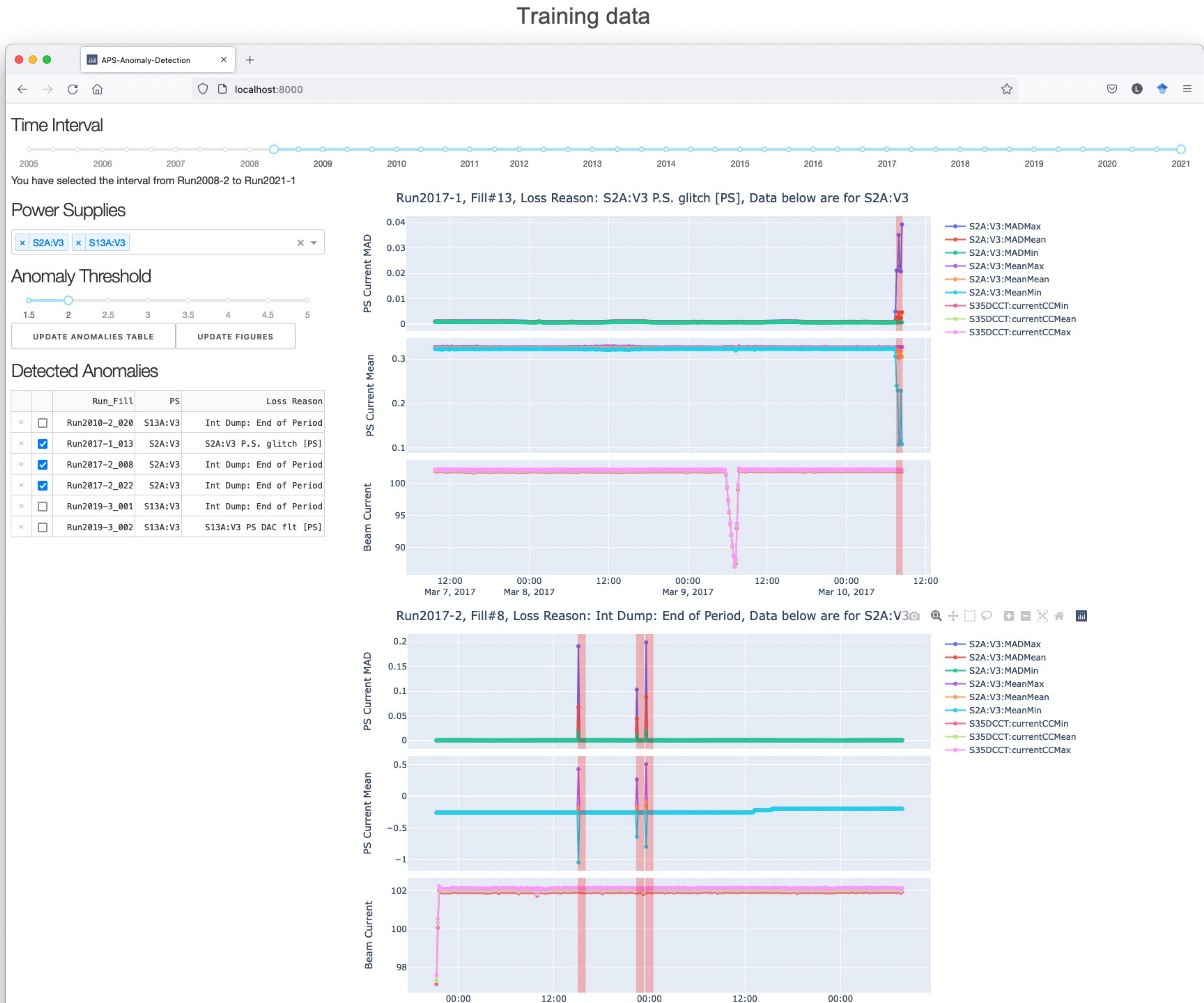
Anomaly Detection in Current Noise Monitor Data

Autoencoder input: 6 timesteps × 6 noise monitor PVs = 36
Autoencoder architecture: 36→12→4→12→36 (for each of 1320 power supplies)

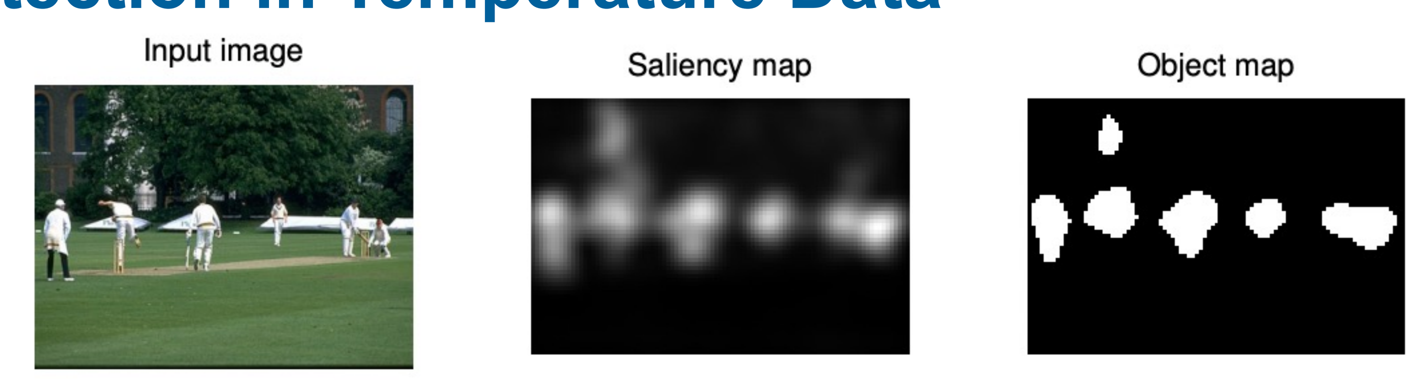
Test data

'Run2015-1', 'Run2015-2', 'Run2015-3', 'Run2016-1', 'Run2016-2', 'Run2016-3', 'Run2017-1', 'Run2017-2', 'Run2017-3', 'Run2018-1', 'Run2018-2'

Training data

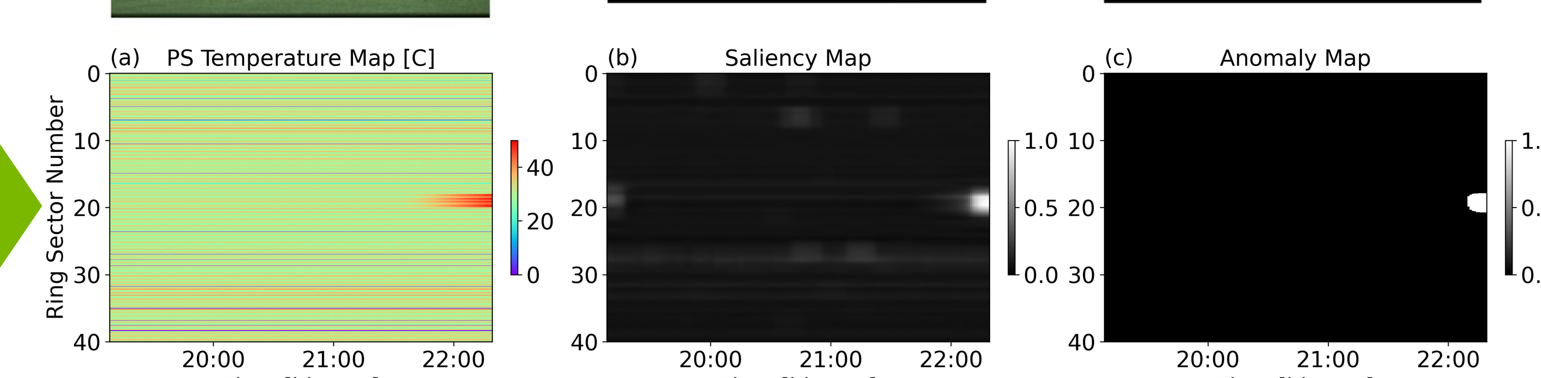


Anomaly Detection in Temperature Data

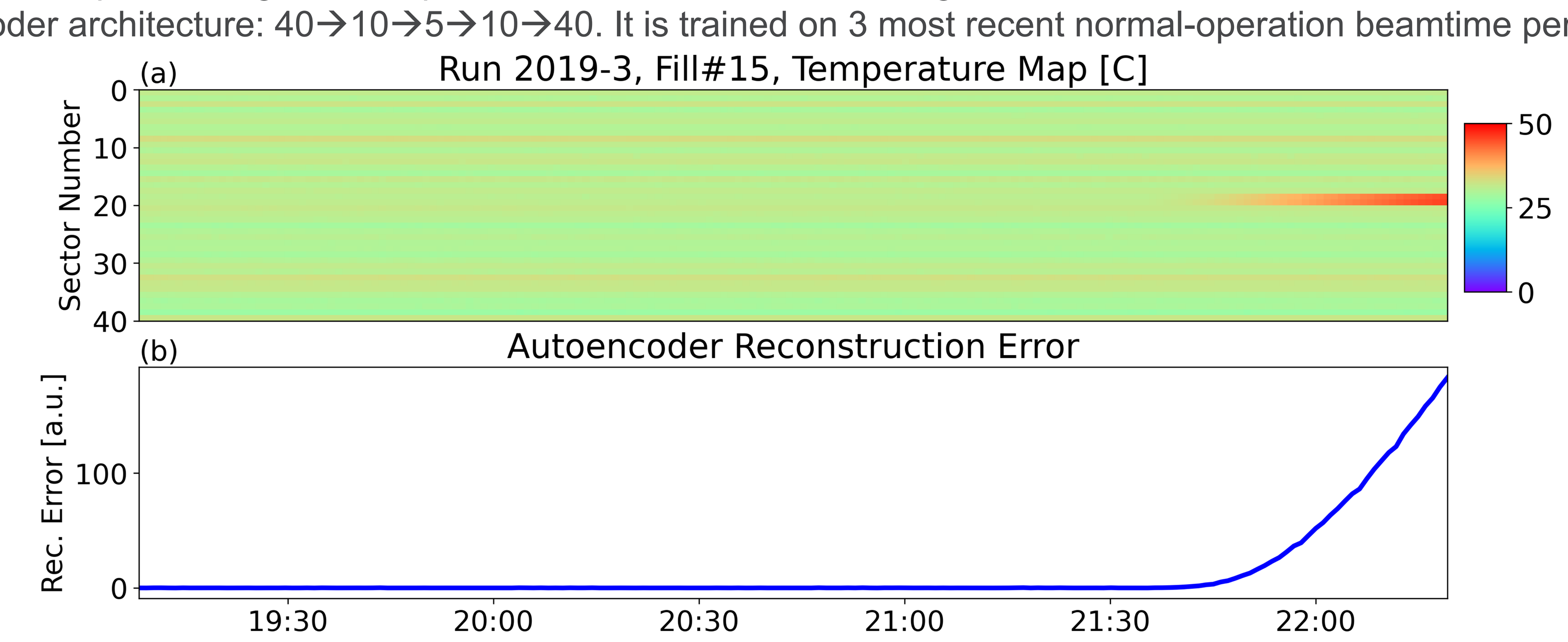


X. Hou and L. Zhang, "Saliency Detection: A Spectral Residual Approach," 2007 *IEEE Conference on Computer Vision and Pattern Recognition*, 2007, pp. 1-8, doi: 10.1109/CVPR.2007.383267.

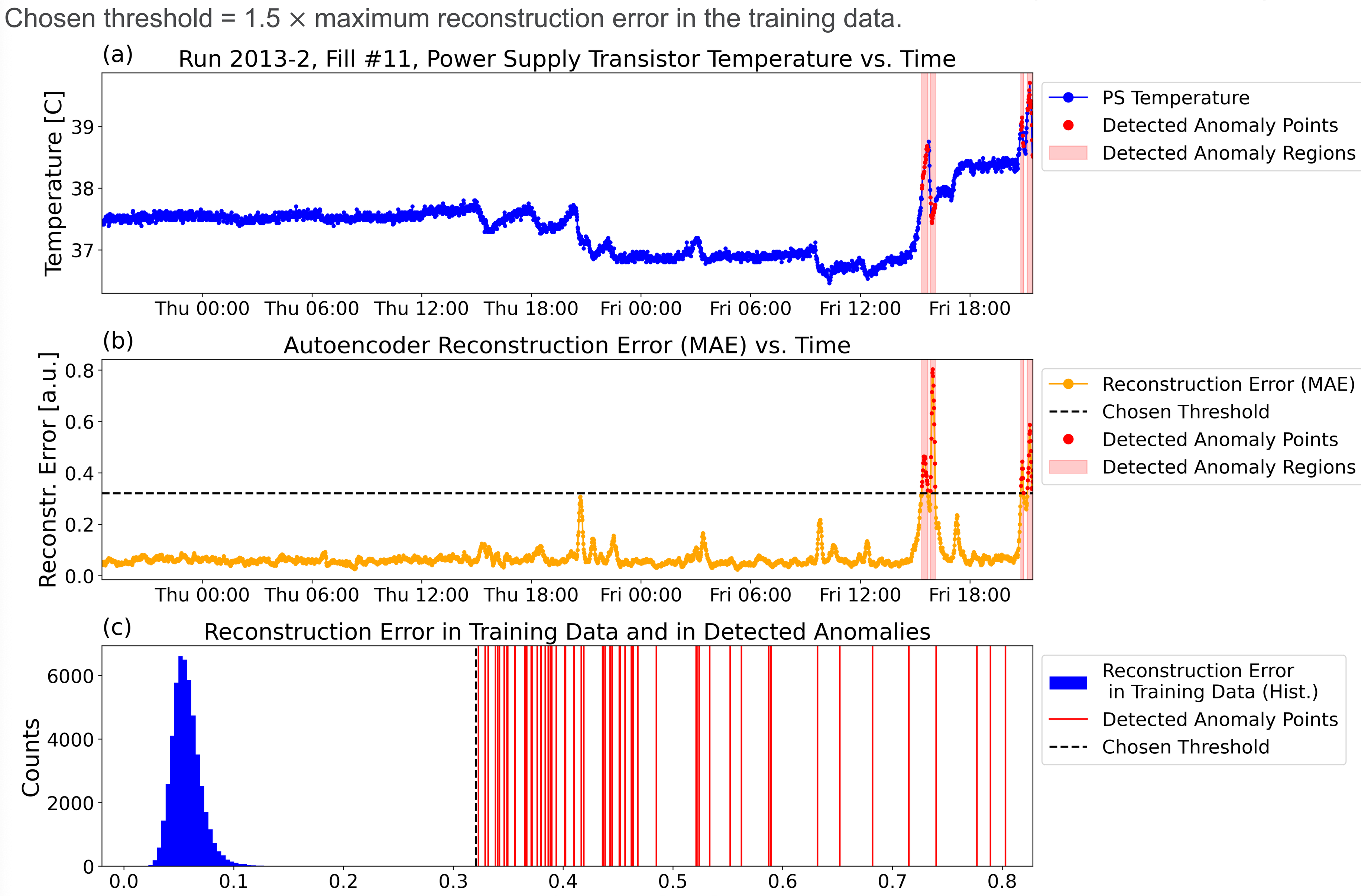
It may be useful in our case



Autoencoder input: average PS temperatures in 40 sectors of the ring
Autoencoder architecture: 40→10→5→10→40. It is trained on 3 most recent normal-operation beamtime periods.



Autoencoder input: S16B:S2:IGBTTempAI at 20 timesteps
Autoencoder architecture: 20→10→5→10→20. It is trained on 10 most recent normal-operation beamtime periods.
Chosen threshold = 1.5 × maximum reconstruction error in the training data.



U.S. DEPARTMENT OF ENERGY

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APS Run History: https://ops.aps.anl.gov/statistics
NN Schematic: https://alexlenail.me/NN-SVG
Anomaly Dashboard: https://plotly.com/dash/

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